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Effectiveness of Carbon Pricing Policy: An Empirical Analysis

Skuteczność polityki ustalania cen dwutlenku węgla – analiza empiryczna

Eyüp Tanıl
Institute of Graduate Studies, Department of Economics, Yalova University, Türkiye
Faculty of Business and Administrative Sciences, Okan University, Türkiye

Mehmet Karakaş
Faculty of Economics and Administrative Sciences, Yalova University, Türkiye

Ali Yasin Kalabak
Faculty of Economics and Administrative Sciences, Yalova University, Türkiye

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Abstract

Carbon taxation has emerged as an effective policy tool for combating global climate change. This study investigates the impact of carbon pricing on carbon emissions and the carbon footprint (CF) in selected countries that were among the first to adopt carbon taxation, using panel data from 1992 to 2021. We apply a range of econometric methods to address specific data challenges, including cross-section dependence tests to explore interdependencies among countries; Delta homogeneity tests to check whether variables are homogeneous across the panel; second-generation panel unit root tests (robust against cross-section dependence) to assess the stationarity of variables; and the Gegenbach et al. [2016] panel cointegration test (robust to both cross-section dependence and heterogeneity) to identify long-term relationships. We also use the panel Dynamic Ordinary Least Squares Mean Group (DOLSMG) estimator to estimate long-run coefficients, considering both heterogeneity across the panel and cross-section dependence. Finally, the Dumitrescu and Hurlin [2012] panel causality test —which also accounts for heterogeneity and cross-section dependence — is employed to examine causal relationships. The results indicate that carbon pricing effectively reduces both carbon emissions and CF. Moreover, the findings reveal a cointegrating relationship among the variables, as well as a unidirectional causal relationship from carbon pricing to both carbon emissions and CF.

Streszczenie

Opodatkowanie emisji dwutlenku węgla stało się skutecznym narzędziem w walce z globalną zmianą klimatu. W omawianym w niniejszym artykule badaniu, wykorzystując dane panelowe z lat 1992–2021, sprawdziliśmy wpływ cen emisji dwutlenku węgla na jego emisję i ślad węglowy w wybranych krajach, które jako pierwsze wprowadziły opodatkowanie emisji dwutlenku węgla. Aby sprostać specyficznym wyzwaniom związanym z danymi, stosujemy wiele metod ekonometrycznych, w tym testy zależności przekrojowych (do zbadania współzależności między krajami), testy homogeniczności Delta (aby sprawdzić, czy zmienne są jednorodne w całym panelu), testy pierwiastków jednostkowych drugiej generacji odporne na zależność przekrojową (do oceny stacjonarności zmiennych) oraz test kointegracji panelowej [Gegenbach et al., 2016] (odporny zarówno na zależność przekrojową, jak i heterogeniczność) w celu identyfikacji długoterminowych zależności. Wykorzy-

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stujemy również estymator panelowy DOLSMG (do oszacowania długoterminowych współczynników), uwzględniając heterogeniczność w całym panelu i zależność przekrojową. Wreszcie do zbadania związków przyczynowo-skutkowych zastosowano test przyczynowości paneli **Dumitrescu i Hurlina** [**2012**], który uwzględnia również heterogeniczność i zależność przekrojową. Uzyskane wyniki wskazują, że ceny emisji dwutlenku węgla skutecznie ograniczają zarówno jego emisję, jak i ślad węglowy. Co więcej, wyniki ujawniają istnienie relacji kointegracyjnej między zmiennymi, a także jednokierunkową zależność przyczynową przebiegającą od cen emisji dwutlenku węgla do jego emisji oraz śladu węglowego.

Introduction

In recent years, policymakers have developed various policy tools to address the growing threat of global warming and combat climate change. In this context, carbon taxation has emerged as an effective instrument in the global effort to mitigate climate change. Numerous empirical studies have evaluated the effectiveness of environmental taxes. However, despite the growing body of research on environmental taxation—particularly carbon taxes—the time periods covered in many studies are relatively short, and the number of empirical analyses focusing specifically on carbon taxation remains limited.

According to **Bayer and Aklin** [**2020**], policymakers, academics, and market participants in Europe have expressed doubts about the effectiveness of carbon pricing in tackling climate change. Many of these concerns focus on carbon prices that remain below anticipated levels, particularly in relation to the societal impact of carbon emissions. This study also aims to contribute to the ongoing debate surrounding carbon pricing policies in Europe.

This research stands out from previous studies in two aspects. First, it covers a long time period, from 1992 to 2021, allowing for a more comprehensive analysis. Second, it examines not only the impact of carbon taxation on carbon emissions but also its effect on the carbon footprint (CF), providing a more holistic perspective on the issue. The study employs a balanced panel data analysis method to investigate the effectiveness of carbon pricing policies in a group of early-adopting countries. We construct separate models for each dependent variable, with the carbon pricing rate serving as the independent variable. Additionally, we include per capita gross domestic product (GDP per capita) as a control variable. Data on CF are obtained from the Global Footprint Network database, while data on per capita carbon emissions (in metric tons), GDP per capita, and carbon pricing are sourced from the World Bank.

The primary aim of the study is to determine whether there is a long-term relationship between carbon pricing and carbon emissions as well as CF, and if so, to identify the direction and coefficients of this relationship. Within this framework, we use the panel data analysis method, which has been frequently employed in recent years. To determine whether there is any cross-sectional dependence among countries, we apply the **Breusch-Pagan** [**1980**], **Pesaran** [**2004**], and **Pesaran et al.** [**2008**] tests. In the next stage, we perform the **Pesaran et al.** [**2008**] delta homogeneity test to decide on the homogeneity status of the slope coefficients. Next, we employ the CIPS (Cross-sectional Augmented Im, Pesaran, and Shin) and CADF (Cross-sectional Augmented Dickey-Fuller) unit root tests, developed by **Pesaran** [**2007**], to determine the stationarity of the series. Subsequently, we apply the panel cointegration test developed by **Gegenbach et al.** [**2016**] to test for the existence of long-term relationships among the variables. We then estimate the long-term coefficients using the DOLS-MG (Dynamic Ordinary Least Squares-Mean Group) estimator proposed by **Pedroni** [**2001**]. Finally, we conclude the empirical analysis by conducting the panel causality test using the **Dumitrescu and Hurlin** [**2012**] approach. The findings of the empirical analysis are broadly consistent with those reported by **Safi et al.** [**2021**] and **Xie and Jamaani** [**2022**], particularly in terms of GDP per capita.

The study consists of four sections, including the introduction. The first section outlines the research topic and its significance. The second section provides a detailed review of the theoretical background and relevant literature. The third section describes the dataset, econometric tests, and the rationale for their selection, along with their mathematical foundations. The final section offers policy recommendations based on the empirical findings about the effectiveness of carbon pricing.

Theory and literature

Global warming and climate change have become some of the most urgent issues on the global agenda over the past century. Due to the heavy reliance on fossil fuel-based energy production, countries have often overlooked environmentally friendly production methods. As a result of the unsustainable consumption of fossil fuels, greenhouse gas emissions have increased worldwide. The accumulation of these gases in the atmosphere has led to a significant increase in global average temperatures. In turn, the melting of glaciers has accelerated, sea levels have risen, and clean water sources have diminished. According to the **Intergovernmental Panel on Climate Change** [**2021**], atmospheric CO_2 concentrations in 2019 reached their highest level in at least 2 million years, while methane (CH4) and nitrous oxide (N2O) concentrations were the highest recorded in the past 800,000 years. Since 1750, CO_2 (47%) and CH4 (156%) concentrations have increased far beyond the natural fluctuations observed over the last 800,000 years, whereas the rise in N_2O (23%) has remained relatively stable. This rapid surge significantly increases the likelihood of global average temperatures exceeding 2ºC by 2100. Additionally, the Global Carbon Project predicts that atmospheric CO_2 concentrations would reach 414.7 ppm in 2021, marking a 50% increase from pre-industrial levels. Although CO_2 emissions from the global energy sector briefly dropped to 31.5 Gt in 2020 amid the pandemic [**International Energy Agency, 2023**], they rebounded to 33.4 Gt in 2021 and soared to a record 36.8 Gt in 2022, underscoring the urgent need for effective mitigation strategies.

Moreover, the potential economic and societal losses from rising greenhouse gas emissions continue to grow. **Munich Re** [**2025**], for example, estimates that climate-related disasters in 2024 led to approximately USD 320 billion in economic losses. Rising temperatures can intensify the frequency and severity of extreme weather events—such as floods, storms, and droughts—thereby increasing costs in sectors including infrastructure, health, and agriculture [**Smith et al., 2014**].

In response to these challenges, the international community has undertaken significant efforts to combat climate change. The Kyoto Protocol, signed in 1997, represented the first global commitment to reducing greenhouse gas emissions [**UNFCCC, 1998**]. In 2015, the Paris Climate Agreement followed, setting the goal of limiting global warming to well below 2 degrees Celsius above pre-industrial levels, and ideally to under 1.5 degrees [**UNFCC, 2015**]. Unlike the Kyoto Protocol, the Paris Agreement aims to reduce greenhouse gas emissions permanently through a more comprehensive and long-term approach. The fundamental difference between the two agreements is that the Kyoto Protocol focuses on reducing emissions, whereas the Paris Agreement aims to eliminate them. Therefore selecting effective measures for emission reduction is of great importance.

In this context, carbon taxes and other environmental taxes have become increasingly central to international policy debates due to their potential to reduce greenhouse gas emissions [**Metcalf, 2019**; **Acemoglu et al., 2016**; **Acemoglu et al., 2012**]. Carbon pricing, in particular, is widely viewed as a key instrument for addressing climate change and achieving the goals of the Paris Agreement [**Lilliestam et al., 2021**]. Carbon pricing has emerged as an effective policy instrument in combating climate change, particularly in selected countries, starting from 1990. This policy aims to internalise the environmental costs of greenhouse gas emissions by imposing a financial cost on carbon emissions. The main objective of carbon pricing policy is to reduce carbon emissions, promote the adoption of low-carbon technologies in industries, increase the use of renewable energy sources, and facilitate the transition to cleaner and more sustainable production processes [**Stiglitz et al., 2017**: 9–10]. Countries can choose from various instruments for carbon pricing. However, they generally implement carbon pricing policy through emissions trading schemes or carbon taxes. In recent years, countries have been using both policy instruments.

Governments can implement carbon pricing in various ways by using it as a fiscal policy instrument. This policy can be applied both at the economy-wide level and specifically targeted to certain sectors, industries or local regions. Local conditions, strategic priorities and needs are key considerations in determining the scope or coverage of policy implementation. The success of carbon pricing policy in reducing environmental pollution depends on the level and coverage of the targeted carbon price. It is generally accepted that high carbon pricing, when implemented on a broad scale, is more effective in reducing emissions. Furthermore, the implementation of carbon pricing at high levels and broad scope also promotes low-carbon development in the long term [World Bank, 2022: 12].

Many governments today are implementing carbon pricing policies to combat climate change and reduce increasing greenhouse gas emissions. Many countries are also planning to implement carbon pricing policies soon. The number of countries implementing carbon tax policies has been increasing, particularly after the 2015 Paris Climate Agreement. In the countries covered by this study, carbon taxes were implemented prior to the 1997 Kyoto Protocol and the 2015 Paris Climate Agreement. Carbon tax was first implemented in Finland in 1990. Then in 1991, it was implemented in Sweden and Norway, and in 1992, it was introduced in Denmark. It can be observed that Sweden, Norway and Finland have implemented carbon pricing policies extensively and have generated significant tax revenue as a result (Table 1).

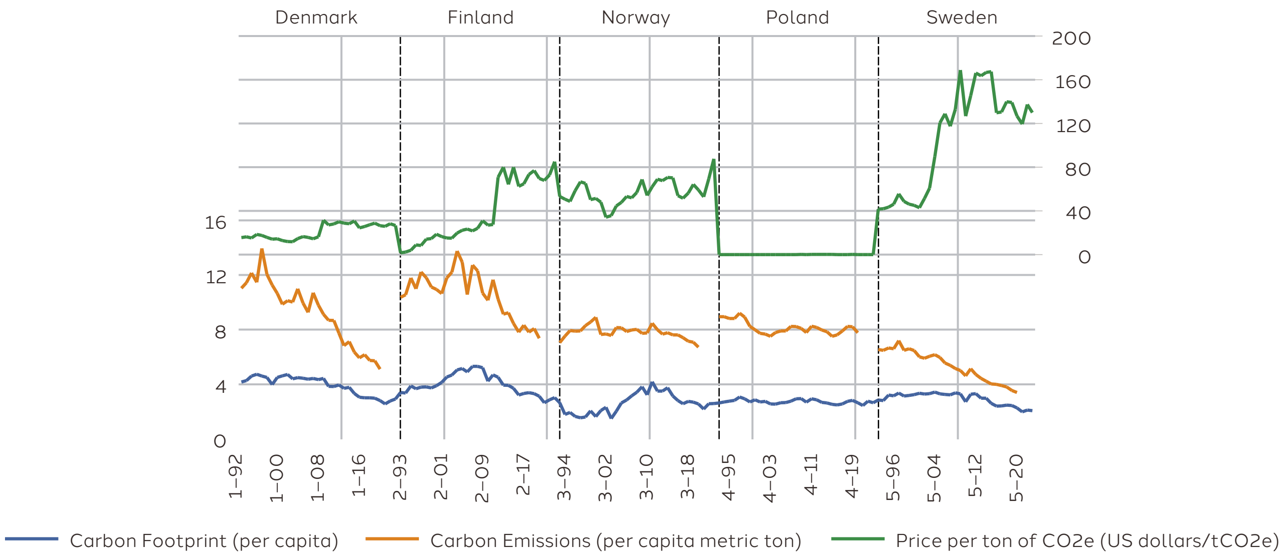
Table 1. Data on carbon tax

Countries	Implementation Year	Covered greenhouse gas emissions [MtCO2e][a]	Covered greenhouse gas emissions [%][b]	Covered national greenhouse gas emissions [%]	Price [US$/tCO2e][c]	Tax Revenue [million US$][d]
Sweden	1991	24	0.05	86.7	125.55	2124.8
Denmark	1992	16	0.03	48.0	26.62/21.90 (fossil fuels and gases)	492.8
Poland	1990	15	0.03	4.1	0.07/14.44 (co2/f-gases)	6.48
Finland	1990	22	0.05	76.0	85.10/58.58 (transport/ other fossil fuels)	1706.7
Norway	1991	43	0.09	98.0	90.86/7.34 (general/ reduced rate)	1800.4

[a] Based on official government sources and/or estimates, [b] Data taken from Köppl and Schratzenster [2022] for the year 2015, [c] represents 2023 carbon prices, [d] represents 2022 carbon tax revenues.

Source: Compiled using data from the World Bank [2023].

Figure 1. Trend of carbon price, carbon emissions, and CF



Note: Price per tonne of CO_2e is displayed on the right vertical axis, while the carbon footprint and carbon emissions are shown on the left vertical axis.

Source: Created based on data obtained from the World Bank [2023].

Figure 1 illustrates the trends over time in carbon emissions, carbon tax, and CF data. Figure 1 shows that carbon taxes generally increase, while carbon emissions and CF decrease. This pattern suggests that carbon taxation has a positive environmental impact. Especially in Finland and Sweden, the successful implementation of carbon tax policies has contributed to a reduction in emissions and a decrease in CF. These data provide visual evidence that carbon taxes are an effective tool for sustainability and can support the achievement of emission reduction targets. Rising carbon tax levels increase the cost of activities that contribute to greenhouse gas emissions and encourage environmentally-friendly practices, such as reducing energy consumption from fossil fuels, transitioning to renewable energy sources, and improving energy efficiency.

Table 2 summarises multiple studies conducted in different countries on the impact of environmental taxes and carbon taxes on carbon emissions. The studies presented in Table 2 vary in their methodologies and findings, but most of them demonstrate the emission-reducing effect of environmental taxes. For example, Safi et al. [2021] provide evidence that an increase in environmental taxes reduces CO_2 emissions both in the short and long term. In another study, Xie and Jamaani [2022] demonstrate the emission-reducing effect of environmental taxes in G-7 countries. However, some studies have obtained different results. For instance, Zaghdoudi and Maktouf [2017] find a positive relationship between environmental taxes and CO_2 emissions. In another study, Saucedo et al. [2017] find a negative relationship between environmental taxes and CO_2 emissions in a fixed-effects model. However, in the same study, they are unable to obtain a significant result based on the GMM estimator.

Table 2. Literature review

Authors	Period, sample and method	Dependent variable	Findings
Gugler et al. [2023]	2013–2015, England, Regression Discontinuity in Time	Co2 Emissions	The study has found a substantial decrease in CO2 emissions (26% or 38.6 MtCO2) in the British energy sector as a result of the carbon tax.
Xie and Jamaani [2022]	1990–2020, G-7 Countries, Method of Moment Quantile Regression and Dumitrescu and Hurlin panel causality	Co2 Emissions	Environmental taxes reduce CO2 emissions by promoting renewable energy and green innovation. Additionally, an increase in GDP leads to an increase in CO2 emissions.
Wolde-Rufael and Mulat-Weldemeskel [2022]	1994–2018, 18 Latin American and Caribbean countries, Panel Data Analysis	Co2 Emissions	Environmental taxes reduce CO2 emissions.
Rafique et al. [2022]	1994–2016, 29 OECD Countries, Panel cointegration and FMOLS Method	Ecological Footprint (EF)	Environmental taxes reduce ecological footprint.
Safi et al. [2021]	1990–2019, G-7, Panel Data Analysis	Co2 Emissions	An increase in environmental taxes reduces CO2 emissions both in the short and long term.
Meireles et al. [2021]	2008–2018, EU Countries, Panel Data Analysis	Co2 Emissions	An increase in transportation taxes reduces CO2 emissions.
Zhang et al. [2020]	2008–2016, China, Difference-in-difference (DID) Method	Co2 Emissions	They find that the Emission Trading System (ETS) policy has successfully reduced industrial CO2 emissions in China's seven pilot regions.
Bayer and Aklin [2020]	2008–2016, EU Countries, Generalized Synthetic Control Method	Co2 Emissions	Even though carbon prices are low (less than 35 euros per tonne), they are still effective in reducing CO2 emissions.
Fernando [2019]	1990–2004, Denmark, Finland, Norway and Sweden, Synthetic Control Method	Co2 Emissions	In Norway and Sweden, CO2 taxes reduce CO2 emissions. However, in Denmark and Finland, the impact of CO2 taxes is not significant.
Hajek et al. [2019]	2005–2015, Denmark, Ireland, Finland, Sweden and Slovenia, Panel Data Analysis	Co2 Emissions	Based on the partial regression coefficient (−0.01158), an increase of one euro per tonne in carbon tax would result in a reduction of annual per capita emissions by 11.58 kg.
Shmelev and Speck [2018]	1960–2010, Sweden, Time Series Analysis	Co2 Emissions	Carbon tax, as well as energy taxes on coal and LPG, contribute to the reduction of carbon emissions.
Zaghdoudi and Maktouf [2017]	1994–2014, OECD, Panel Threshold Regression	Co2 Emissions	There is a positive relationship between environmental taxes and CO2 emissions.

Authors	Period, sample and method	Dependent variable	Findings
Saucedo et al. [**2017**]	1994–2014, OECD, Static and Dynamic Panel Data Analysis	Co2 Emissions	According to the Fixed Effects Model, there is a negative relationship between environmental taxes and per capita CO2 emissions. However, in dynamic panel data analysis, the environmental tax does not have a significant effect on CO2 emissions.
Kotnik et al. [**2014**]	1995–2010, EU-19 Countries, Panel Data Analysis	Co2 Emissions	Environmental taxes directly and indirectly impact greenhouse gas emissions negatively.
Miller and Vela [**2013**]	1995–2010, Developed and developing countries, Panel Data Analysis	Co2 Emissions	An increase in environmental taxes reduces CO2 emissions.
Morley [**2012**]	1995–2006, EU Countries and Norway, Panel Data Analysis	Co2 Emissions	There is a negative and significant relationship between environmental taxes and environmental pollution.
Lin and Li [**2011**]	1990–2008, Denmark, Finland, Netherlands, Norway, Sweden, Difference in difference	Co2 Emissions	The results indicate that the carbon tax in Finland has led to a 1.7% decrease in per capita CO2 emissions. In Denmark, Sweden, and the Netherlands, negative effects on emissions were observed, but they were not statistically significant.

Source: Authors' own elaboration.

In the literature, we can see that researchers generally investigate the impact of environmental taxes on CO_2 emissions. Despite this, we observe that there is a limited number of studies specifically focused on carbon taxes. Examples of such studies include **Zhang et al.** [**2020**], **Gugler et al.** [**2023**], Gemechu et al. [2014], **Bayer and Akalin** [2012], **Hajek et al.** [2019], **Lin and Li** [2012], and **Shmelev and Speck** [**2018**]. These studies demonstrate the mitigating effect of carbon taxation on CO_2 emissions. The literature summary in Table 2 indicates that environmental taxes, including carbon taxation, generally have a mitigating effect on CO_2 emissions. These findings reinforce the argument that policy instruments such as environmental taxes and carbon pricing are effective in reducing carbon emissions.

Data and method

We construct two models to measure the impact of carbon taxes on CF and CO_2 emissions in selected countries between 1992 and 2021, using annual data in both models. In the first model, the dependent variable is CO_2 emissions, and in the second, it is CF. In this study, Denmark, Finland, Norway, Poland, and Sweden are included because they were among the earliest adopters of carbon taxes. We select these countries to explore long-term relationships in panel data, as a sufficiently long time dimension is essential for such analyses. Consequently, Model 1 covers a time dimension of 30 and a cross-sectional dimension of 5, whereas Model 2 covers a time dimension of 28 and a cross-sectional dimension of 5. The analysis begins in 1992, the first year in which all the studied countries had a carbon tax in place. Model 1 ends in 2019 due to the unavailability of CO_2 emissions data for later years, while Model 2 ends in 2021 because per capita GDP data are unavailable thereafter. Given the time frame of the study, we believe that the missing observation for the GDP per capita variable for one year would not significantly alter the analysis results. Equations 1 and 2 represent the first and second models respectively.

$$Co2_{it} = \alpha_0 + \alpha_1 GDPer_{it} + \alpha_2 CPrice_{it} + \in_{it} \tag{1}$$

$$CF_{it} = \alpha_0 + \alpha_1 GDPer_{it} + \alpha_2 CPrice_{it} + \in_{it} \tag{2}$$

In both equations, t, i and $\in_{it}$ represent the period, the cross-sections, and the error term respectively. In equation 1, $Co2_{it}$ represents the dependent variable, which denotes per capita CO_2 emissions. In equation 2, CF_{it} represents the CF, symbolising the dependent variable. In both equations, the independent variable, $CPrice_{it}$, represents the price paid per tonne of carbon dioxide equivalent (CO_2e) emissions in dollars. Lastly, the variable $GDPer_{it}$, included as a control variable in both equations, represents per capita gross domestic product (GDP). Table 3 shows detailed descriptions of the variables and the database from which they were obtained.

Table 3. Description of Variables

Variables	Description	Unit	Source
$Co2_{it}$	Carbon emission	Per capita metric ton	World Bank
CF_{it}	Carbon footprint[1]	Per capita	Global Footprint Data
$CPrice_{it}$	Price per tonne of CO2e	US Dollars/tCO2e	World Bank
$GDPer_{it}$	Per capita GDP	US Dollars at 2015 prices	World Bank

Source: Authors' own elaboration.

There are two carbon pricing rates in the World Bank [2023]. The reason for this distinction is that countries apply carbon taxes to different sectors at different rates over time. In the study, we use a carbon price rate of 1 for each year between 1992 and 2021, considering complete data available for the countries' annual carbon pricing.

We use balanced panel data analysis, which allows for analysis with multiple cross-sectional units. To determine the impact of increasing globalisation in recent years, we first conduct tests for cross-sectional dependence. These tests are Breush and Pagan [1980] LM, Pesaran [2004] CD_{LM} and Pesaran et al. [2008] bias-adjusted LM. Panel data analyses conducted without considering cross-sectional dependence may lead to unreliable results [Destek et al., 2018; Hsiao, 2014: 347].

The Breusch-Pagan LM test was developed to test the relationship between units based on the fixed effects model. The null hypothesis of the Breusch and Pagan [1980] LM test for cross-sectional dependence is that there is no cross-sectional dependence among the error terms of the regression equation. The LM statistic of the test is calculated through Equation 3.

$$CD_{lm} = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{p}_{ij}^{2} \tag{3}$$

Pesaran [2004] developed the CD (Cross-Sectional Dependence) test as an alternative to the Breusch-Pagan LM test. The CD test is designed to provide consistent results in both N>T and N<T situations, addressing the inconsistency issue of the LM test when N>T. In this test, the null hypothesis (Ho) is that there is no cross-sectional dependence. The test provides two test statistics based on pairwise correlation coefficients to be used in both balanced and unbalanced panels. Since this study is based on balanced panel data analysis, we only present the balanced panel CD test statistic in Equation 4.

$$CD = \sqrt{\frac{2T}{N(n-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{p}_{iJ}\right) \tag{4}$$

Pesaran, Ullah, and Yamagata [2008] developed a modified version of the Breusch and Pagan [1980] LM test by incorporating various adjustments and additions to address the issue of biased results when N>T. Equation 5 represents the calculation of the test statistic of this modified version [Pesaran et al., 2008].

$$LM_{adj} = \sqrt{\frac{2}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\frac{(T-K)\hat{p}_{ij}^{2}-\mu_{T_{ij}}}{\upsilon_{T_{ij}}} \tag{5}$$

[1] The carbon footprint measures CO_2 emissions associated with fossil fuel use. In Ecological Footprint accounts, these amounts are converted into biologically productive areas necessary for absorbing this CO_2. The carbon footprint is included in the Ecological Footprint because it is a competing use of bioproductive space, since increasing CO_2 concentrations in the atmosphere are considered to represent a build-up of ecological debt. Some carbon footprint assessments express results in tonnes released per year, without translating this amount into area needed to sequester it.

Performing panel data analysis without considering slope heterogeneity can lead to biased results in panel cointegration and long-term coefficient estimation. We apply the delta homogeneity test developed by **Pesaran and Yamagata** [**2008**] to test for slope heterogeneity. In this test, there are two test statistics: $\hat{\Delta}$ test for large samples and $\hat{\Delta}_{adj}$ for small samples. The null hypothesis in this test is that the slope coefficient is homogeneous. Equation 6 shows the calculation of the test statistics.

$$\hat{\Delta} = \sqrt{N}\left(\frac{N^{-1}\hat{s} - k}{\sqrt{2k}}\right),\ \hat{\Delta}_{adj} = \sqrt{N}\frac{(N^{-1}\hat{S} - 2k)}{\sqrt{var(\hat{z}_{iT})}} \tag{6}$$

According to **Hsiao** [**2014**], conducting statistical tests without considering the stationarity of the series leads to unreliable results and may cause the problem of spurious regression. In addition, to test for the presence of a long-term relationship between variables, it is necessary for the variables to be stationary in first differences. For all these reasons, we apply the cross-sectionally augmented ADF (CADF) and IPS (CIPS) tests, which are commonly used in the literature, as developed by **Pesaran** [**2007**]. These tests, which can be applied in the case of cross-sectional dependence, are referred to as second-generation unit root tests in the literature. The null hypothesis of the test is that the series is non-stationary. Equation 7 displays the calculation of the test statistic for the CADF unit root test.

$$\Delta Y_{it} = y_i + \ y_i Y_{i,t-1} + y_i \bar{X}_{t-1} + \sum_{i=0}^{p} Y_{it} \Delta \bar{Y}_{t-1} + \sum_{i=0}^{p} Y_{it} \Delta Y_{i,t-1} + \in_{it} \tag{7}$$

In equation 7, $Y_{i,t-1}$ represents the average lagged value of the parameter, and $\Delta Y_{i,t-1}$ represents the cross-sectional averages of the first-order differences. Additionally, equation 8 shows the calculation of the CIPS test statistic.

$$\widehat{CIPS} = \frac{1}{N}\sum_{i=1}^{n} CADF_i \tag{8}$$

In this equation, CIPS represents the cross-sectionally augmented IPS test, and CADF represents the cross-sectionally augmented Dickey-Fuller test.

Finding the variables to be stationary after taking the first difference suggests the possibility of a long-term relationship among the series. For this purpose, we apply the panel cointegration test developed by **Gegenbach, Urbain, and Westerlund** [**2016**] to detect the long-term relationship among the series. This error correction-based test provides effective results against heterogeneity and cross-sectional dependence. Additionally, this test allows for unit-specific lag lengths. The test is based on the vector error correction model presented in equation 9, which utilises the common factor structure [**Gegenbach et al., 2016**].

$$\Delta y_i = d\delta_{y.x_i} + \alpha_{y_i} y_{i,-1} + \omega_{i,-1} + \nu_i \pi_i + \varepsilon_{y.x_i} = \alpha_{y_i} y_{i,-1} + g_i^d + \varepsilon_{y.x_i} \tag{9}$$

In the first stage of the test, the OLS estimation of the model is obtained for each unit, and the null hypothesis H_0: $\alpha_{y_i} = 0$ is tested using a t-test. The $(T-1-p)\times(T-1-p)$ dimensional projection matrix is defined as shown in equation 10.

$$M_A = I_{T-1-p} - A(A'A)A' \tag{10}$$

Equations 11 and 12 represent the OLS estimator and variance of αy_i respectively.

$$\hat{\alpha}_{yi} = \frac{y'_{i,-1} M_{g_i^d} \Delta y_i}{y'_{i,-1} M_{g_i^d} y_{i,-1}} \tag{11}$$

$$\sigma^2_{\hat{\alpha}_{y_i}} = \frac{\sigma^2_{y.xi}}{y'_{i,-1} M_{g_i^d} y_{i,-1}} \tag{12}$$

The expansion of $\sigma^2_{y,xi}$ in the numerator of equation 12 is $T^{-1}(\Delta y_i - \hat{\alpha}_{yi} y_{i,-1})' M_{g_i^d} (\Delta y_i - \hat{\alpha}_{yi} y_{i,-1})$ Equation 13 shows the calculation of the t-statistic.

$$t_{c_i} = t_{\alpha_{y_i}} = \frac{\hat{\alpha} y_i}{\hat{\sigma}_{\hat{\alpha} y_i}} \tag{13}$$

The panel test statistic is obtained by taking the average of the unit-specific t-statistics. Equation 14 represents the calculation of the panel test statistic.

$$\bar{t}_c = \frac{1}{N} \sum_{i=1}^{N} t_{c_i} \tag{14}$$

The null hypothesis of the cointegration test is "H_0: there is no cointegration relationship among the series."

To estimate the coefficients of the long-term relationship among the variables obtained from the cointegration test, we use the DOLSMG estimator, which provides robust results in the presence of cross-sectional dependence and heterogeneity [**Pedroni, 2001**]. In the DOLSMG estimator proposed by **Pedroni** [**2001**], it is based on the model presented in Equation 15.

$$Y_{it} = \mu_i = \beta_i X_{it} + u_{it} \quad i = 1, \ldots, N \quad t = 1, \ldots, T \tag{15}$$

The model in Equation 15 indicates that the cointegration model is heterogeneous across units. In the first stage, the cointegration model given in Equation 15 is estimated for each unit using the dynamic ordinary least squares (DOLS) approach with the inclusion of lagged values and leads. Subsequently, the results are combined for the entire panel using the **Pesaran and Smith** [**1995**] MG approach.

$$\hat{\beta}_{DOLSMG} = N^{-1} \left[\sum_{i=1}^{N} \left(\sum_{t=1}^{T} (Z_{it} Z'_{it}) \right)^{-1} \right] \left(\sum_{t=1}^{T} (Z_{it} \bar{y}_{it}) \right) \tag{16}$$

In Equation 16, Z_{it} represents the vector of explanatory variables, and $Y_i = Y_{it} - \bar{Y}_i$. Equation 17 illustrates the calculation of the DOLSMG test statistic.

$$t_{\hat{\beta}_{DOLS,i}} = N^{-1} \sum\nolimits_{t=1}^{T} t_{\beta_{DOLS,i}} \tag{17}$$

For the detection of causality between series, we use the **Dumitrescu and Hurlin** [**2012**] test, which is an extension of the Granger causality test. This test is commonly used in the literature for panels with cross-sectional dependence and heterogeneity [**Lopez, Weber, 2017**]. Equation 18 shows the basic regression of the **Dumitrescu and Hurlin** [**2012**] panel causality test.

$$y_{it} = \alpha_i + \sum_{k=1}^{k} \gamma_i^{(k)} Y_{it-k} + \sum_{k=1}^{K} \beta_i^{(k)} X_{it-k} + \varepsilon_{it} \tag{18}$$

In Equation 18, $X_{i,t}$ and $Y_{i,t}$ represent two stationary variables. The parameters in the equation may vary across the cross-sections, but they are assumed to be time-invariant. K represents the lag length. The hypotheses of the **Dumitrescu and Hurlin** [**2012**] panel causality test are as follows:

- H_0: There is no causality.
- H_a: There is causality.

To test the null hypothesis, the Wald Test statistics calculated for each cross section are summed and averaged. Equation 19 shows the calculation of the Wald test statistics.

$$\bar{W}_{N,T} = \frac{1}{N} \sum_{i=1}^{N} W_{i,T} \tag{19}$$

In the Dumitrescu and Hurlin [2012] panel causality test, when T is large, the test statistic specified in equation 20 is used.

$$\bar{Z}_{N,T} = \sqrt{\frac{N}{2K}}(\bar{w}_{N,T} - K) \xrightarrow{T,\, N \to \infty} N(0,\, 1) \quad (20)$$

Empirical findings and discussion

Before analysing cointegration and causality in econometric research, it is standard practice to first examine whether the variables exhibit unit roots. To determine which panel unit root tests are appropriate, one must assess both the homogeneity of the variables and the presence of cross-sectional dependence. According to the results shown in Table 4, all three tests suggest the presence of cross-sectional dependence in the models. Determining the homogeneity of slope coefficients is necessary to identify the appropriate estimation methods in the subsequent stage.

Table 4. Cross Section Dependency Test Results

	MODEL 1		MODEL 2	
Test	Statistics	p-value	Statistics	p-value
LM	52.13	0.0000	51.12	0.0000
LM adj*	25.76	0.0000	26.21	0.0000
LM CD*	4.524	0.0000	5.705	0.0000

Source: Authors' own elaboration.

According to the results presented in Table 5, the slope coefficients of both models are found to be heterogeneous. This indicates that the impact of explanatory variables on the dependent variables differs among the analysed cross-sections. Such heterogeneity may stem from the varying structural characteristics and policy contexts among the countries. Recognising these differences is crucial, and we take them into account in the subsequent tests to ensure more accurate and robust results.

Table 5. Results of Pesaran and Yamagata [2008] Delta Test

	MODEL 1		MODEL 2	
Test	Statistics	p-value	Statistics	p-value
$\hat{\Delta}$	10.118	0.0000	11.402	0.0000
$\hat{\Delta}_{adj}$	10.928	0.0000	12.247	0.0000

Source: Authors' own elaboration.

Table 6. Results of the CADF and CIPS Unit Root Test

	Variables	CIPS				CADF			
		Constant		Constant & Trend		Constant		Constant & Trend	
		I (0)	I (1)	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
MODEL 1	$Co2_{it}$	−1.910	−5.137*	−2.657	−5.269*	−1.447	−3.964*	−2.060	−4.045*
	$CPrice_{it}$	−1.944	−4.835*	−1.929	−4.860*	−1.870	−3.420*	−1.812	−3.404*
	$GDPer_{it}$	−0.854	−3.389*	−1.501	−3.738*	−1.419	−2.790*	−1.828	−3.225*
MODEL 2	CF_{it}	−1.096	−5.341*	−2.806***	−5.431*	−0.932	−3.766*	−2.234	−3.827*
	$CPrice_{it}$	−2.030	−5.068*	−1.866	−5.084*	−1.968	−3.504*	−1.660	−3.498*
	$GDPer_{it}$	−1.249	−3.986*	−2.101	−4.250*	−1.476	−3.088*	−2.007	−3.517*

Note: *, **, and *** represent significance levels of 1%, 5%, and 10% respectively. The CADF test statistic is the t-bar statistic used in balanced panel data.

Source: Authors' own elaboration.

According to the CIPS and CADF test results in Table 6, all variables exhibit unit roots at their levels. However, after taking first differences, each series becomes stationary, indicating that all variables are integrated of order one (I (1)). Consequently, we perform a cointegration test that takes both heterogeneity and cross-sectional dependence into account, allowing us to more rigorously investigate whether a long-term relationship exists among these variables.

Table 7 shows that in both models, the null hypothesis H_0 is rejected at the 0.01 and 0.05 significance levels respectively. In other words, there exists a cointegration relationship among the variables. Similar studies support these findings. For example, Akkaya and Hepsağ [2021], examining data from Turkey spanning 1985 to 2018, identify a long-run relationship between fuel taxes and carbon emissions. Likewise, Loganathan et al. [2014] confirm a long-run relationship between carbon taxes and carbon emissions in Malaysia. However, Telatar and Birinci [2022], using non-linear time series analysis with annual data from Turkey (1994–2019), do not find evidence of long-run cointegration among environmental indicators, the ecological footprint, and carbon emissions. Since our study establishes a long-run relationship among these variables, we proceed to estimate long-run coefficients to gain deeper insights into the nature and magnitude of these relationships.

Table 7. Results of Gegenbach et al. [2016] Panel Cointegration Test

d. y	Coefficients	T-bar Statistics	P-value	
$Y(t-1)$	−0.787	−3.741	<=0.01	MODEL 1
$Y(t-1)$	−0.602	−3.372	<=0.05	MODEL 2

Note: We determine the lag length heterogeneously.

Source: Authors' own elaboration.

Table 8. Results of the Long-Term Coefficient Estimation

Country	Variables	MODEL 1		MODEL 2	
		Beta	t-statistic	Beta	t-statistic
Denmark	$CPrice_{it}$	0.05440	1.137	0.05122	5.661*
	$GDPer_{it}$	0. 0004265	0.9397	0.0000674	−0.7776
Finland	$CPrice_{it}$	−0.02247	−2.124*	−0.007417	−2.535*
	$GDPer_{it}$	0.000436	3.942*	0.0002532	7.586*
Norway	$CPrice_{it}$	−0.05828	−3.393*	−0.04008	−2.691*
	$GDPer_{it}$	−0.000254	−2.094*	−0.0001252	−1.224
Poland	$CPrice_{it}$	−0.06263	−6.19*	−0.0131	−2.048*
	$GDPer_{it}$	0.000135	2.323*	0.0000982	2.63*
Sweden	$CPrice_{it}$	−0.01531	−8.454*	−0.008183	−5.631*
	$GDPer_{it}$	0.000192	5.195*	0.0000316	1.124
The entire panel	$CPrice_{it}$	−0.02086	−8.507*	−0.003511	−3.295*
	$GDPer_{it}$	0.0001872	4.609*	0.0000381	4.176*

Note: The critical value for $\alpha = 0.05$ is 1.96.

Source: Authors' own elaboration.

According to the findings in Table 8, the beta coefficients of the panel groups are statistically significant because their absolute t-statistic values are greater than the critical t-table value. In Model 1, a unit increase in $CPrice_{it}$ decreases $Co2_{it}$ by 0.02086 units, while a unit increase in $GDPer_{it}$ increases $Co2_{it}$ by 0.0001872 units. In Model 2, a unit increase in $CPrice_{it}$ decreases CF_{it} by 0.003511 units, while a unit increase in $GDPer_{it}$ variable increases CF_{it} by 0.0000381 units. As shown in Table 8, for Model 1, the coefficient of $CPrice_{it}$ is negative and statistically significant in Finland, Norway, Poland, and Sweden. In other words, an increase in $CPrice_{it}$ leads to a decrease in $Co2_{it}$ in these countries. The findings of Model 2 are consistent with those of Model 1. They imply that carbon pricing is an effective policy tool in reducing both carbon emissions and the carbon footprint. In our study, only in Model 2 does carbon pricing increase the carbon footprint in Denmark. This may be due to Denmark's exemptions for the manufacturing and energy sectors in the implementation of its carbon tax. Finally, the results for the overall panel are in line with the existing literature.

As shown in Table 9, in Model 1, we detect causality from $CPrice_{it}$ to $Co2_{it}$, from $Co2_{it}$ to $GDPer_{it}$, and from $CPrice_{it}$ to $GDPer_{it}$. In Model 2, we identify causality from $CPrice_{it}$ to CF_{it} and from $CPrice_{it}$ to $GDPer_{it}$. These findings corroborate the DOLSMG estimator results for the overall panel. In other words, there is a unidirectional causal relationship between carbon pricing and the dependent variables. This suggests that fluctuations in carbon pricing influence not only environmental indicators but also economic outcomes, highlighting its role as a critical policy instrument. Loganathan et al. [2014], Mehta and Derbeneva [2024], and Dogan et al. [2022] report similar findings.

Table 9. Results of the Dumitrescu and Hurlin [2012] Panel Causality Test

MODEL 1			MODEL 2		
Direction	Test Statistics	P-value	Direction	Test Statistics	P-value
$CPrice_{it}$ => $Co2_{it}$	2.7682	0.0263	$CPrice_{it}$ => CF_{it}	4.3356	0.0000
$Co2_{it}$ => $CPrice_{it}$	1.4640	0.1432	CF_{it} => $CPrice_{it}$	1.2288	0.2191
$GDPer_{it}$ => $Co2_{it}$	0.2316	0.8168	$GDPer_{it}$ => CF_{it}	–0.7238	0.4692
$Co2_{it}$ => $GDPer_{it}$	2.2314	0.0257	CF_{it} => $GDPer_{it}$	0.4855	0.6273
$CPrice_{it}$ => $GDPer_{it}$	5.6878	0.0000	$CPrice_{it}$ => $GDPer_{it}$	2.5374	0.0112
$GDPer_{it}$ => $CPrice_{it}$	–0.8786	0.3796	$GDPer_{it}$ => $CPrice_{it}$	–0.9636	0.3434

Note: In the Dumitrescu and Hurlin panel causality test, we make the series stationary by taking their first differences. We set the lag value to 1. Since T>N, we use the $\bar{Z}_{N,T}$ statistic.

Source: Authors' own elaboration.

The main findings of this study indicate that carbon and environmental taxes effectively reduce carbon emissions and carbon footprints, aligning with the existing literature. Similar conclusions are reported by Gugler et al. [2023], Xie and Jamaani [2022], Wolde-Rufael and Mulat-Weldemeskel [2022], Safi et al. [2021], Bayer and Akalın [2020], Hajek et al. [2019], Shmelev and Speck [2018], Kotnik et al. [2014], Miller and Vela [2013], and Morley [2012].

However, some studies yield different results. For instance, Saucedo et al. [2017] find a negative relationship between environmental taxes and per capita carbon emissions in a fixed-effects model but do not observe a statistically significant relationship in a dynamic panel data analysis. Similarly, Lin and Li [2011] report that carbon tax reduces per capita carbon emissions in Finland but has no statistically significant effect in Denmark, Sweden or the Netherlands.

Zaghdoudi and Maktouf [2017], using panel data for OECD countries, find a positive relationship between environmental taxes and carbon emissions. Likewise, Loganathan et al. [2014] identify a positive relationship between carbon taxes and carbon emissions, although this relationship is not statistically significant.

Conclusion

This study investigates the impact of carbon pricing policy on carbon emissions and the carbon footprint. While the impact of environmental taxes on carbon emissions has been widely studied, their effect on the carbon footprint is generally overlooked. Moreover, research focusing specifically on carbon taxes remains limited and often covers relatively short time periods. In this context, our study stands out by investigating the impact of carbon pricing policy on both carbon emissions and the carbon footprint over an extended time period. The use of a balanced panel data methodology further allows for the analysis of long-term relationships among the variables. In these respects, we believe the study makes a significant contribution to the literature. In these contexts, we believe that the study makes a significant contribution to the literature. The main limitations of the study are as follows:

- Sample size: Only five countries are included. Although many countries have adopted carbon pricing policies, the balanced panel data analysis method used to capture long-term relationships requires the inclusion of countries that implemented such policies early and share geographic and cultural similarities.
- Time period: The study aims to cover the years 1992–2022. However, due to the unavailability of CO_2 emissions data beyond 2019 and per capita GDP data beyond 2021, the most recent years could not be included.

The findings of the analysis are particularly relevant for shaping government carbon tax policies. Various countries, such as Italy, Hungary, Greece, and Turkey, are considering introducing carbon taxes. This study provides a projection for governments considering carbon taxation. One possible reason for their hesitation may be concerns about the potential negative effects of carbon taxes on production costs. To address this, governments could use carbon tax revenues to incentivise companies to transition to more environmentally friendly production methods. Moreover, carbon tax revenues can help increase public income and finance government expenditures. When designing such taxes, policymakers may consider adopting "carrot-based" rather than "stick-based" approaches to enhance taxpayer acceptance. A more inclusive, incentivising, and participatory policy design that considers taxpayer perspectives could reduce resistance to carbon taxation.

Beyond its environmental function, carbon taxation can also play a crucial role in promoting social justice by ensuring fairer tax collection across different social classes. This could be achieved by taxing luxury goods and services that generate significant carbon emissions—for example, private jet travel, large fuel-consuming vehicles and energy-intensive homes. Higher taxes on carbon-intensive luxury consumption by wealthier groups could align environmental sustainability with social equity objectives.

Ultimately, the design of such a policy should consider factors such as feasibility, effectiveness, and social acceptance. Comprehensive analysis and stakeholder collaboration are essential for evaluating its potential impacts. Fair determination of tax rates is key to achieving environmental goals while maintaining public support. Additionally, the economic effects of the policy, its role in industrial transformation, and social protection mechanisms should be considered.

Future research should therefore focus on refining and evaluating this policy proposal, while incorporating feedback from all relevant stakeholders. The greater the level of consensus and collaboration achieved, the more effective and inclusive environmental taxation will become.

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